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Ambient Air Pollution and Socioeconomic Status in China

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Background: Air pollution disparities by socioeconomic status (SES) are well documented for the United States, with most literature indicating an inverse relationship (i.e., higher concentrations for lower-SES populations). Few studies exist for China, a country accounting for 26% of global premature deaths from ambient air pollution.

Objective: Our objective was to test the relationship between ambient air pollution exposures and SES in China.

Methods: We combined estimated year 2015 annual-average ambient levels of nitrogen dioxide (NO_2) and fine particulate matter [PM $\leq$2.5 μm in aerodynamic diameter ($PM_{2.5}$)] with national demographic information. Pollution estimates were derived from a national empirical model for China at 1-km spatial resolution; demographic estimates were derived from national gridded gross national product (GDP) per capita at 1-km resolution, and (separately) a national representative sample of 21,095 individuals from the China Health and Retirement Longitudinal Study (CHARLS) 2015 cohort. Our use of global data on population density and cohort data on where people live helped avoid the spatial imprecision found in publicly available census data for China. We quantified air pollution disparities among individual's rural-to-urban migration status; SES factors (education, occupation, and income); and minority status. We compared results using three approaches to SES measurement: individual SES score, community-averaged SES score, and gridded GDP per capita.

Results: Ambient NO_2 and $PM_{2.5}$ levels were higher for higher-SES populations than for lower-SES population, higher for long-standing urban residents than for rural-to-urban migrant populations, and higher for the majority ethnic group (Han) than for the average across nine minority groups. For the three SES measurements (individual SES score, community-averaged SES score, gridded GDP per capita), a 1-interquartile range higher SES corresponded to higher concentrations of 6–9 $\mu g/m^3$ NO_2 and 3–6 $\mu g/m^3$ $PM_{2.5}$; average concentrations for the highest and lowest 20th percentile of SES differed by 41–89% for NO_2 and 12–25% for $PM_{2.5}$. This pattern held in rural and urban locations, across geographic regions, across a wide range of spatial resolution, and for modeled vs. measured pollution concentrations.

Conclusions: Multiple analyses here reveal that in China, ambient NO_2 and $PM_{2.5}$ concentrations are higher for high-SES than for low-SES individuals; these results are robust to multiple sensitivity analyses. Our findings are consistent with the idea that in China's current industrialization and urbanization stage, economic development is correlated with both SES and air pollution. To our knowledge, our study provides the most comprehensive picture to date of ambient air pollution disparities in China; the results differ dramatically from results and from theories to explain conditions in the United States. https://doi.org/10.1289/EHP9872

Introduction

Ambient air pollution causes ~4 million deaths per year (Cohen et al. 2017; Lelieveld et al. 2015; Lim et al. 2012), yet the disease burden is not evenly distributed across individuals, communities, countries, regions, or demographic groups. Between-country disparities in ambient air pollution are well documented (Brauer et al. 2016; Cohen et al. 2017); in contrast, within-country disparities, including how ambient pollution levels correlate with socioeconomic status (SES) and other demographic attributes, are poorly studied other than in the United States and a few other high-income countries. Much of the existing literature documents disparities for specific locations (e.g., in a specific city). A smaller body of literature documents disparities nationwide for the United States (Bell and Ebisu 2012; Clark et al. 2014, 2017; Liu et al. 2021; Miranda et al. 2011). The vast majority of the literature indicates, for North America, higher pollution levels for low-SES than for high-SES communities and individuals (Clark et al. 2014, 2017; Hajat et al. 2015; Liu et al. 2021; Table S2 of Marshall et al. 2014; Marshall 2008); evidence for European countries is more limited and suggests a mixed relationship (Hajat et al. 2015; Temam et al. 2017). Limited knowledge exists for China or other low- or middle-income countries (Hajat et al. 2015), where 91% of the premature deaths from outdoor air pollution occur (26% are in China) (Cohen et al. 2017; WHO 2021). Less than 20% of the Chinese population lives in cities that meet the national annual fine particulate matter [PM $\leq$2.5 μm in aerodynamic diameter ($PM_{2.5}$)] standard (the GB 3095-2012 standard; 35 $\mu g/m^3$) (China MEE 2016), and none live in cities meeting the World Health Organization's (WHO) annual guideline (5 $\mu g/m^3$) (Song et al. 2017; Xu et al. 2019a; Zhang and Cao 2015). Publicly available census data for China are relatively coarse [county level (县级); average per county: 0.4 million people; 2,642 km^2]; this limits the potential for some census-based demographic/air pollution analyses in China that, in the United States, are common.

The environmental inequality patterns in the United States are generally explained in part by past and present racial discrimination and race- and class-based market dynamics: Low-SES communities lack social capital and political power and access and are therefore less able to stop locally undesirable land uses such as highways, industry, and other sources of pollution (Brulle and Pellow 2006; Hajat et al. 2015; Lane et al. 2022; Tessum et al. 2019, 2021; Marshall et al. 2014). Longstanding residential segregation by race and income adds to the potential for disparities (Chambliss et al. 2021). Racism by private individuals (e.g., racial covenants on the sale of property) and systemically by private companies (e.g., banks' lending practices) and by local, state, and national government (e.g., redlining) in the past and present has supported and accelerated exposure disparities (Bullard 2008;

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Rothstein 2017; Lane et al. 2022). The net result in the United States is disproportionate air pollution burdens for low-SES communities and individuals, with well-documented theory to explain those disparities.

Yet, theories developed in the United States may not be applicable for China and elsewhere owing to the different historical, social, economic, political, urbanization, and industrialization characteristics (Guo et al. 2020; Jian 2005; Ma 2010). For example, others have found that environmental inequality patterns in European countries are different from the United States owing to the lower extent of social segregation and the greater tendency (relative to in the United States) for lower-SES groups to live on the outskirts of the city (Temam et al. 2017). Urban expansion patterns (Cesaroni et al. 2010), local housing policy (Havard et al. 2009), and discrete choice between benefits/amenities and negative aspects of the environment (Padilla et al. 2014) are also found to influence the exposure inequality patterns in Europe. A study in India proposed an environmental Kuznets curve [EKC; i.e., a theory that environmental degradation first rises and then falls with an increasing per capita income (Cole et al. 1997; Stern 2004; Marcotullio et al. 2005)] -like pattern (i.e., a U-shaped relationship), where marginalized communities are excluded from negative and positive externalities of industrial development (Kopas et al. 2020).

As the world's largest developing economy, China has in recent decades experienced rapid urbanization (Liang and Yang 2019; Zhang and Song 2003), increased income disparities (Li et al. 2013; Xie and Zhou 2014), and widespread rural-to-urban migration (Chan 2013; Chan and Zhang 1999; Zhang and Song 2003). Secondary (manufacturing) industry represents a large proportion of gross national product (GDP) in China (in 2018, 41% in China vs. 19% in the United States); cities or places with more industry and manufacturing jobs tend to be of higher income, on average, and potentially also experience more air pollution (Chen et al. 2018; Li et al. 2019). In addition, with comparatively (relative to in the United States, on average) larger city size and population density, more-centralized urban structure, and poorer traffic conditions (Liu and Wang 2016; Wu et al. 2006), people in China tend to live (on average, relative to in the United States) closer to their workplace (Chen et al. 2008). Those strong aspects in regional and urban form reflect differing housing preferences and civil infrastructure (e.g., transportation systems) (Zheng and Kahn 2008); they also reflect differences in history in China relative to the United States [e.g., China did not experience "White flight"—an exodus of affluent White people in the United States, largely starting in the 1950s and 1960s, from urban to suburban communities (Rothstein 2017)]. The net result is, in China, a comparatively higher concentration of high-SES population in urban centers (often with higher air pollution levels) and lower-SES population in outskirts and suburban areas (Guo et al. 2020; Wu 2002; Xiao 2016). These many conditions support the hypothesis that, unlike in the United States, in China air pollution exposures might be higher for high-SES than for low-SES populations.

Previous studies in China have investigated air pollution inequality with respect to specific sources, including industrial emissions (He et al. 2019; Ma 2010; Schoolman and Ma 2012), emissions from electric vehicles (Ji et al. 2015), and household consumption (Zhao et al. 2019a). Studies on ambient concentrations (Guo et al. 2020; Huang et al. 2019; Li et al. 2018; Zhao et al. 2018) have focused on a single city or yielded inconclusive results (Xu et al. 2019b; Shen et al. 2020; Wang and Komonpipat 2020). The lack of comprehensive research on environmental inequality in China, including theories and national empirical studies of SES and ambient air pollution, are important gaps in the literature.

Here we put forward an alternative hypothesis (i.e., distinct from the EKC theory, described above) that, in China, higher-SES populations are more exposed to ambient air pollution than are lower-SES populations. We test the hypothesis using ambient annual-average NO_2 and $PM_{2.5}$ levels in China. To test our hypothesis, we conduct multiple national investigations of air pollution disparities by SES, including for individual- and area-level measures of SES, based on ambient air pollution levels for two pollutants: NO_2 and $PM_{2.5}$.

Materials and Methods

For clarity and precision, where a specific term is used from a survey or data set, that term is provided in English and in the original language (Mandarin).

Individual SES Characteristics and Migration Status

To obtain spatially explicit demographic information on a group of individuals, we employ data from the 2015 China Health and Retirement Longitudinal Study (CHARLS) (Zhao et al. 2014). CHARLS is an interview-based nationally representative survey of people in China ≥45 years of age and their spouses ($n = 21{,}095$; see Liu et al. 2017 for CHARLS locations). All participants in CHARLS gave informed consent, and the protocol was approved by the ethical review committee at Peking University. We obtained each individual's highest education attainment (hereafter, education), occupation, and household annual per capita income in yuan (hereafter, income) from the survey. Education was classified as *a*) illiterate, *b*) *sishu*/home school and below, *c*) elementary school, *d*) middle school, or *e*) high school and above. Occupation was categorized according to people's lifetime profession instead of the current working status (given that some people were retired): Individuals who have only done agricultural work (have never done nonagricultural work for >10 d) in their lifetime were classified as engaging in agricultural work; those who have ever done nonagricultural jobs for >10 d (no matter whether they also have done agricultural work) were classified as engaging in nonagricultural work. Income was calculated for each household (shared by the sample individuals on the same household) and is presented as the net post-tax income. The household total annual income includes *a*) household members' wages, bonus incomes, or pensions, and *b*) household agricultural, self-employed activities, public transfer, and other types of transferred income (e.g., from parents, children, relatives). Household per capita income was calculated by dividing the household total annual income by family size.

In addition to the three SES variables that we mainly focused on (education, occupation, income), we also investigated each individual's ethnicity (民族; sometimes also translated as "nationality," but referring to group identification, not citizenship) and household per capita living expenditure (hereafter, expenditure). According to the 2020 census (National Bureau of Statistics of China 2021), China is officially composed of 56 ethnic groups, with Han as the dominant group (91.1% of the total population) and the other 55 groups as minorities (少数民族) (combined, 8.9% of the total population). Clusters of people who are ethnic minorities are found in the bordering northwest (e.g., Uygur), north (e.g., Mongol), northeast (e.g., Manchu), south (e.g., Zhuang), and southwest (e.g., Tibet), with some in the central interior (e.g., Hui). In the CHARLS survey, there are 10 ethnic categories: Han (汉族, 92.3% of CHARLS respondents), Hui (回族, 0.5%), Zhuang (壮族, 1.0%), Uyghur (维吾尔族, 0.5%), Yi (彝族, 0.5%), Tibet (藏族, 0.9%), Miao (苗族, 0.6%), Mongol (蒙古族, 1.1%), Dai (傣族, 0.2%), and other (2.6%) (CHARLS 2015). Expenditure was calculated for each household (household annual total expenditure divided by family size) using the CHARLS survey. Total expenditure included weekly expenditure on food and restaurants; monthly expenditure on communication, utilities, transportation, household and personal items, entertainment, and housekeepers; and yearly expenditure on clothing, traveling, heating, furniture, education, medical, fitness and beauty, automobile, taxes and donations, and others.

We separately considered each individual's rural/urban migration status by combining each respondent's household location [urban districts (区, urban) vs. rural counties (县, rural) within the prefecture-level cities] and *hukou* (户口) status. *Hukou* is the official household registry system that records a citizen's location-of-origin and determines local residence rights, such as medical care, unemployment benefits, school enrollments, and public housing (Chan and Zhang 1999; Zhang and Treiman 2013). Importantly, *hukou* is *a*) typically unchanged during a person's life even if that person moves and *b*) assigned as nonagricultural (非农业户口; i.e., urban) or agricultural (农业户口; i.e., rural). [Since 2014, the Chinese government has in some cases initiated the canceling of the *hukou* system; although the binary *hukou* classification still dominates in most places, some people's *hukou* is "unified residence," i.e., a single/combined category that sidesteps the urban/rural distinction. Survey respondents who indicated unified residence *hukou* (统一居民户口; $n=346$, 1.6%) or no *hukou* (没有户口; $n=31$, 0.1%) have been excluded here.] Because rural-to-urban migrants cannot enjoy many social benefits (e.g., medical care), the *hukou* system discourages that migration and also puts such migrants at a disadvantage relative to urban residents with a nonagricultural *hukou* (Afridi et al. 2015; Liu 2005; Whalley and Zhang 2007; Wu and Treiman 2007; Zhao 1999). We employed three rural/urban migration categories: urban resident (i.e., with a nonagricultural *hukou*); rural-to-urban migrant (i.e., an urban resident with an agricultural *hukou*); and rural resident (i.e., with an agricultural *hukou*). [An urban-to-rural migrant—i.e., someone who lives in a rural area but with a nonagricultural *hukou*—is uncommon (<3% of our data set) and not included in this analysis.]

We also considered population density at the individual's household location as a control variable in our analysis. Population density was determined at the community level, using the population count in the community divided by total area of the community. The community information was collected from the CHARLS 2011 community survey (CHARLS 2013).

Constructing Three SES Matrices

As described next, we obtained three SES matrices to represent demographic conditions at the individual and areal levels in China, and then compared the results across methods. Using multiple independent approaches to quantifying SES sheds additional light on the questions considered and informs whether results are robust to the methods employed.

1. An individual-level SES was derived from CHARLS data using a standardized SES score reflecting education, occupation, and income; the approach reflects factor analysis of mixed data (FAMD), which is a principal component analysis method applicable to data sets with both quantitative and qualitative variables (Kolenikov and Angeles 2004; Vyas and Kumaranayake 2006). We use the "MissMDA" package in R to handle missing values (see above for category classifications), then "FactoMineR" to perform FAMD: education and occupation as categorical variables, income (log-transformed) as quantitative. An individual's SES ($n=21,095$) is defined here as the normalized scores of the first FAMD dimension (explaining 30% of the total variance; see Figure S1 and Table S1 for weights and contributions for income and each category of education and occupation). A higher score represents a higher SES.
2. An area-level SES was derived from CHARLS data by aggregating individual SES to the community-level average. "Community" (村;社区) is a formally defined geographic unit, used in the census and for mail systems; it is the smallest de facto administration level in China. As defined in the 2011 (baseline year) CHARLS survey, CHARLS individuals are from 450 communities, including 237 rural communities [also termed villages (村); located in rural counties] and 213 urban communities (社区; i.e., located in urban districts).
3. A second area-level SES reflects per capita GDP (1-km^2 resolution). These data were derived by combining year 2015 national gridded GDP predictions based on nighttime lights and population images (Zhao et al. 2017) (1-km^2 resolution) and the WorldPop year 2015 population density data set (Stevens et al. 2015) (30 arc seconds resolution, or ~ 1 km^2 at the equator). We resampled the population density data set to match the coordinates of the gridded GDP data set using a bilinear interpolation approach and then divided the gridded GDP by the resampled population density to calculate the GDP per capita. To investigate the air pollution disparities at multiple spatial resolutions, we also resampled the raster layer of GDP per capita and averaged it to different grid sizes (2, 5, 10, 20, 50, and 100 km; after removing grid cells with zero or missing values, the number of grid cells for the 1-km grid and each of those six grid sizes were $n=3,861,463$, $n=1,058,301$, $n=204,565$, $n=61,863$, $n=18,985$, $n=3,953$, and $n=1,220$, respectively).

As mentioned above, one of the motivations for using three distinct approaches was to avoid the spatial coarseness of census data. Other motivations included shedding deeper light on the question and informing whether the result is robust to the different methods employed. Each of these three demographic data sets was then combined with ambient air pollution concentrations, as described next.

NO_2 and $PM_{2.5}$ Ambient Concentrations

For all three SES data sets, we employed as our ambient air pollution metric the annual-average concentrations of two pollutants (NO_2 and $PM_{2.5}$). Pollution concentrations were derived from national empirical models for China (Xu et al. 2019a). The models incorporated monitoring data, satellite observations, universal kriging, and predictor data, such as land use, traffic, and meteorological data (Table S2). Model predictions were year 2015 annual-average concentrations at 1-km^2 resolution [9.6 million cells; 10-fold cross-validation R^2: 0.78 (NO_2), 0.89 ($PM_{2.5}$)] (Xu et al. 2019a). In sensitivity analyses (below), we used the monitoring data directly [i.e., excluding the empirical models of Xu et al. (2019a)].

For the individual-level CHARLS analyses, concentrations were estimated using the empirical models for that individual's residential location (longitude and latitude recorded during the interview). For community-level CHARLS analyses, concentrations were estimated using the average individual-level concentration within each community. For GDP per capita, we resampled the GDP per capita data set to the same grid as the pollution data using bilinear interpolation and then matched the two data sets to derive GDP per capita on the 1-km pollution grid. The CHARLS demographic data, GDP per capita data, and pollution estimation data from the empirical models all were for year 2015. For sensitivity analyses regarding spatial resolution, we resampled the pollution data into the 2-, 5-, 10-, 20-, 50-, and 100-km grids, as described above for GDP per capita.

Quantifying Air Pollution Disparities by Each SES Factor

We focused on NO_2 and $PM_{2.5}$. Those two pollutants were selected because they are important and widely tracked (both are criteria pollutants); both have important health effects associated with exposures (e.g., Beelen et al. 2014; Kaufman et al. 2016; Lu et al. 2015; Pope et al. 2011); and, importantly, publicly available national models exist for the two pollutants (Xu et al. 2019a). Investigating two pollutants provides additional testing of the hypothesis investigated.

For an individual's migration status and each factor that contributes to SES (i.e., education, occupation, and income), we determined relationships with ambient concentrations, considering both unadjusted and fully adjusted effects. Unadjusted effects were determined by comparing the means and quantiles (10th, 25th, 50th, 75th, and 90th) of NO_2 and $PM_{2.5}$ concentrations for the samples in each migration and SES group (here, we grouped income using quintiles; any missing group for each variable was also included in our analysis). Specifically, for migration status and SES factors, we calculated the maximum differences (both absolute and relative differences, with absolute values) in NO_2 and $PM_{2.5}$ concentrations between the group averages and the population averages. We also determined the unadjusted effects for population density at household locations (grouped into tertiles).

Adjusted effects were determined using two sets of regression models: One set comprised multivariate ordinary least squares regression models that included only individual-level factors (migration status, education, occupation, income, and age) as independent variables; the other set comprised multilevel mixed-effects linear regression models that also included prefecture-city (地级市; usually including both urban districts and rural counties) random intercepts to control for city clustering effects. In the multilevel mixed-effect models, we also included population density at the household locations as a control variable. In both models, migration status, education, and occupation were treated as categorical variables. To achieve normality, income data were log-transformed and then standardized to the whole study population; parameter estimates referred to a 1-unit increase in the z-score for the log of income. All regressions were run only on individuals with complete data [$n=15{,}197$; 72% of the CHARLS cohort; incomplete data ($n=5{,}898$; 28%) were excluded from the regressions]; results are reported in terms of best-estimate values and 95% confidence intervals (CIs). To investigate potential bias due to missing data, we performed sensitivity tests using the multiple imputation approach (Horton and Lipsitz 2001), which creates several imputed data sets by replacing missing values with imputed values and combining the results obtained from each of them. We used the *mice* package in R to generate five imputed data sets using probable means methods and then calculated the pooled regression results of the five imputed data sets for both individual-level multivariate regression models and prefecture-city random intercepts regression models.

In sensitivity tests, we also investigated the unadjusted and adjusted relationships between ethnicity and household per capita living expenditure and ambient concentrations. For ethnicity, the unadjusted effects were determined for the 10 ethnic groups; for the adjusted effects, we created a dummy variable for ethnic minorities (i.e., individuals who are not Han), and included it in individual-level multivariate regression models and multilevel mixed-effects regression models with prefecture-city random intercepts. For expenditure, the unadjusted effects were determined for each quintile; for the adjusted effects, we included the log-transformed and standardized (to the whole study population) expenditure in both individual-level and multilevel models.

Metrics Quantifying Air Pollution Disparities by Individual SES Score, Community SES Score, and Gridded GDP per Capita

We quantified disparities using two metrics. The first metric involved linear regressions of concentration on SES score or GDP per capita (log scale). Here, we calculated the regression slopes multiplied by the interquartile ranges (IQRs) of SES (SES score, log of GDP per capita) to quantify the air pollution disparities between high- and low-SES groups. The second metric involved the (absolute and relative) disparity in mean NO_2 and $PM_{2.5}$ concentrations between the population with the highest 20% and the lowest 20% SES (population weighted for GDP per capita). To better visualize the disparity patterns for each subgroup of the total population (see below for subgroup classifications), we also calculated the mean pollution concentration and mean SES (SES score, log of GDP per capita) for each 10% of the subsample.

For the individual-level SES score, disparities were quantified on the overall populations as well as separately for three values for migration status. In sensitivity analyses, we separately quantified disparities in five geographic regions in China (Figure S2); this approach reflects geographic variability as well as, implicitly, economic development and climate conditions. For the community-averaged SES score, we quantified the disparities across all communities and by urban communities and rural villages separately. For gridded GDP per capita, we quantified the disparities on overall grids and by urban/rural grid cells. Urban/rural cells were defined according to the spatial cities of China in 2015 from Beijing City Lab (Long 2016) using community boundaries and urban built-up areas. The urban/rural classifications were done using the *mask* function in the Python "rasterio" package (mask 1-km gridded GDP using urban definition shapefiles). Grid cells *a*) with the centers inside the urban definition shapefiles or *b*) selected by Bresenham's line algorithm (which determines which points on a two-dimensional raster should be selected to form a close approximation to a straight line between two given points) were designated as urban; all other grid cells were defined as rural. To investigate whether the results were robust to the specific urban/rural definition employed, we also conducted sensitivity tests using three alternative urban/rural land classifications: *a*) township population density in year 2010 (Wu et al. 2015), *b*) a neighborhood-level vector cellular automata model (this model reproduces global patterns and behavior from local interactions of cells, representing the cells as a collection of interconnected irregular geographic objects) based on density, neighborhood condition, and other spatial variables for year 2012 (Long et al. 2016), and *c*) a 300-m resolution global land cover map (GLOBCOVER) data set (Bontemps et al. 2011), which is based on satellite images. All four urban definition shapefiles were downloaded from Beijing City Lab (Beijing City Lab 2014). In our approaches, individuals/communities/grids were included in either urban or rural areas.

In addition, separately, we conducted sensitivity analyses quantifying the disparities using six alternative spatial resolutions from 2 to 100 km (vs. 1 km in the main analysis). The motivation was to see whether environmental inequality patterns differed across spatial scales of analysis.

Sensitivity Analysis Using Monitored Concentrations

To test the robustness of results using modeled concentrations, as a sensitivity analysis we employed monitoring data directly (i.e., excluding the empirical model). By definition, this analysis was restricted to locations with a monitor (i.e., the 1-km grid cells containing a monitor; $n=1{,}466$, see Figure S3 for the spatial distribution of the monitor locations). The population-weighted average concentrations (in micrograms per meter cubed) for NO_2 and $PM_{2.5}$ (37 and 55 $\mu g/m^3$, respectively) at monitor locations were higher than the national averages (28 and 53 $\mu g/m^3$), especially for NO_2. However, the GDP per capita (population weighted; in yuan) at monitor locations (mean = 16,847; median = 13,408) was lower than the population average (mean = 59,080; median = 24,691). Below, we give separate results for all monitor locations ($n = 1{,}466$), urban monitor locations ($n = 1{,}076$; 73% of monitors), and rural monitor locations ($n = 390$; 27%). Comparing the modeled vs. monitored concentrations, the model performance was similar in both urban and rural locations for both two pollutants [regression R^2: 0.88 (NO_2), 0.95 ($PM_{2.5}$) for urban monitor locations, and 0.89 (NO_2), 0.95 ($PM_{2.5}$) for rural monitor locations].

Results

Based on the individual data (CHARLS cohort), average ambient air pollution concentrations at home locations were 24 $\mu g/m^3$ (IQR: 18–31) for NO_2 and 51 $\mu g/m^3$ (38–60) for $PM_{2.5}$. Those values are several times higher than the WHO annual mean guidelines for NO_2 (10 $\mu g/m^3$) and $PM_{2.5}$ (5 $\mu g/m^3$) (WHO 2021). The proportion of the population exceeding the WHO guideline was 97% for NO_2 and 100% for $PM_{2.5}$.

Consideration of individuals' urban migrant status and SES groups (Figure 1; Table S3) revealed the following. For NO_2, mean concentrations for rural residents (22 $\mu g/m^3$) and rural-to-urban migrants (26 $\mu g/m^3$) were lower than for urban residents (31 $\mu g/m^3$); for $PM_{2.5}$, mean concentrations were nearly identical for rural residents (50 $\mu g/m^3$) and rural-to-urban migrants (also 50 $\mu g/m^3$; a <2% difference), which were slightly lower than for urban residents (55 $\mu g/m^3$). In univariate consideration of all three SES variables (education, occupation, and income), NO_2 and $PM_{2.5}$ concentrations were generally higher for higher-SES groups (i.e., higher education, nonagricultural work, higher income) than for lower-SES groups, which is consistent with the hypothesis described in the "Introduction" section. The maximum concentration disparity percentage (with absolute value) between group means and the population average was 28% for migrant status and 12–18% for SES groups, for NO_2; for $PM_{2.5}$, analogous relative disparities were 8% and 3–7%. NO_2 and $PM_{2.5}$ concentrations were both higher for individuals in middle- and high-population density communities and lower for low population density communities (Table S3). Air pollution disparities by SES variables generally held even controlling for migrant status (Figure S4). In individual-level fully adjusted models and city random intercept regression models (Table S4), the generally positive relationships still held (except for education in the city random intercept model for $PM_{2.5}$, which had nonsignificant negative slopes for higher education groups), and many but not all SES variables were statistically significant. In multiple imputation models (Table S5), the positive relationships generally held; the regression coefficients for both individual-level models and multilevel models did not change substantially (differences were generally <10%).

Results by ethnicity (Tables S6 and S7) indicate that, relative to the population-average exposure for NO_2 and $PM_{2.5}$ (24 and 51 mg/m^3, respectively), average exposures were nearly the same for people who are Han (25 and 52 mg/m^3, respectively; that finding was expected because the overall population is 92% Han), higher for people who are Hui (39 and 67 mg/m^3, respectively) or Uyghur (58 mg/m^3 for $PM_{2.5}$), and lower for people in each of the remaining seven groups [and, for Uyghur for NO_2 (21 mg/m^3)]. (Average SES scores were higher-than-average for people who are Hui or Uyghur, and lower-than-average for the remaining seven minority groups; thus, results by ethnicity were generally consistent with the finding above that average NO_2 and $PM_{2.5}$ exposures in China were higher than average for upper-SES individuals.) Considering all people in any one of the nine ethnic minority groups, average exposures were 25% lower (NO_2) and 24% lower ($PM_{2.5}$) than the overall population average. For the adjusted effects models, including ethnic minority status as a dummy (i.e., binary) variable yielded a negative coefficient for both pollutants in the individual-level fully adjusted models and a nonsignificant coefficient in the city random intercept models. That finding implies that the lower ambient concentrations for ethnic minorities are mainly due to the concentration differences in the cities they live (i.e., a between-city, rather than a within-city, effect).

The unadjusted results by expenditure (Table S8) indicate that NO_2 concentration was higher for individuals with higher expenditure (23 vs. 26 $\mu g/m^3$, respectively, for the 20% of individuals with the lowest and highest expenditure); there was no significant relationship between $PM_{2.5}$ concentration and expenditure (50–51 $\mu g/m^3$ for all quintiles of expenditure); the mean SES scores were higher for individuals with higher expenditure. For the adjusted effects models (Table S7), expenditure had a slightly positive coefficient for NO_2 in the city random intercept model, a negative coefficient for $PM_{2.5}$ in the individual-level model, and nonsignificant coefficients in the two other models ($PM_{2.5}$, city-random-intercept; NO_2 individual-level model). The generally positive relationships for urban migration status and the three major SES variables (education, occupation, and income) still held after controlling for ethnicity and expenditure.

The three SES approaches (Figure 2A–C) revealed a consistent pattern: Ambient air pollution concentrations at home locations were higher for high-SES than for low-SES individuals or areas across methods, pollutants, and urban–rural status, again suggesting that the findings here are generally consistent with the hypothesis offered in the "Introduction" section. According to linear regression models of concentrations vs. SES, at 1-km resolution, a 1-IQR higher SES corresponded to a higher concentration of 5.6 $\mu g/m^3$ NO_2 (95% CI: 5.4, 5.9), 3.5 $\mu g/m^3$ $PM_{2.5}$ (95% CI: 3.0, 3.9) for individual-level data (Table S9); 9.4 $\mu g/m^3$ NO_2 (95% CI: 7.9, 10.8), 6.0 $\mu g/m^3$ $PM_{2.5}$ (95% CI: 3.3, 8.8) for community-level data (Table S10); and 7.3 $\mu g/m^3$ NO_2 (95% CI: 7.1, 7.4), 4.1 $\mu g/m^3$ $PM_{2.5}$ (95% CI: 4.1, 4.2) for GDP per capita (log scale) (Table S11). Those results, rounded and presented as a range, suggest that a 1-IQR higher SES is associated with a range of 6–9 $\mu g/m^3$ NO_2 and 3–6 $\mu g/m^3$ $PM_{2.5}$ higher concentration of air pollution (expressed as a percentage of the population-weighted mean exposure: 23–39% NO_2, 7–12% $PM_{2.5}$). Results by subregion (Figure S5, Table S12) were generally consistent with Figure 2, with a small number of exceptions ($PM_{2.5}$ in central and northern China).

Disparities were larger for community-level than for individual-level data (Tables S9 and S10). For example, average concentrations for the highest and lowest 20th percentage of SES differed by 41% (NO_2) and 12% ($PM_{2.5}$) for individual-level CHARLS data, compared with 89% (NO_2) and 25% ($PM_{2.5}$) for community-aggregated CHARLS data. This finding reflects in part that within- and between-community variabilities of SES were similar in magnitude, whereas variability in modeled concentrations was less within-community than between-community (Table S13). Area-level data reflect the average of the community, and averaging reduces the overall variability more for SES than for ambient concentrations. Air pollution concentrations and SES were higher in urban than rural areas. The positive concentration–SES relationships ($p < 2 \times 10^{-16}$) held even when using different definitions of urban/rural land (Table S11 and Figure S6).

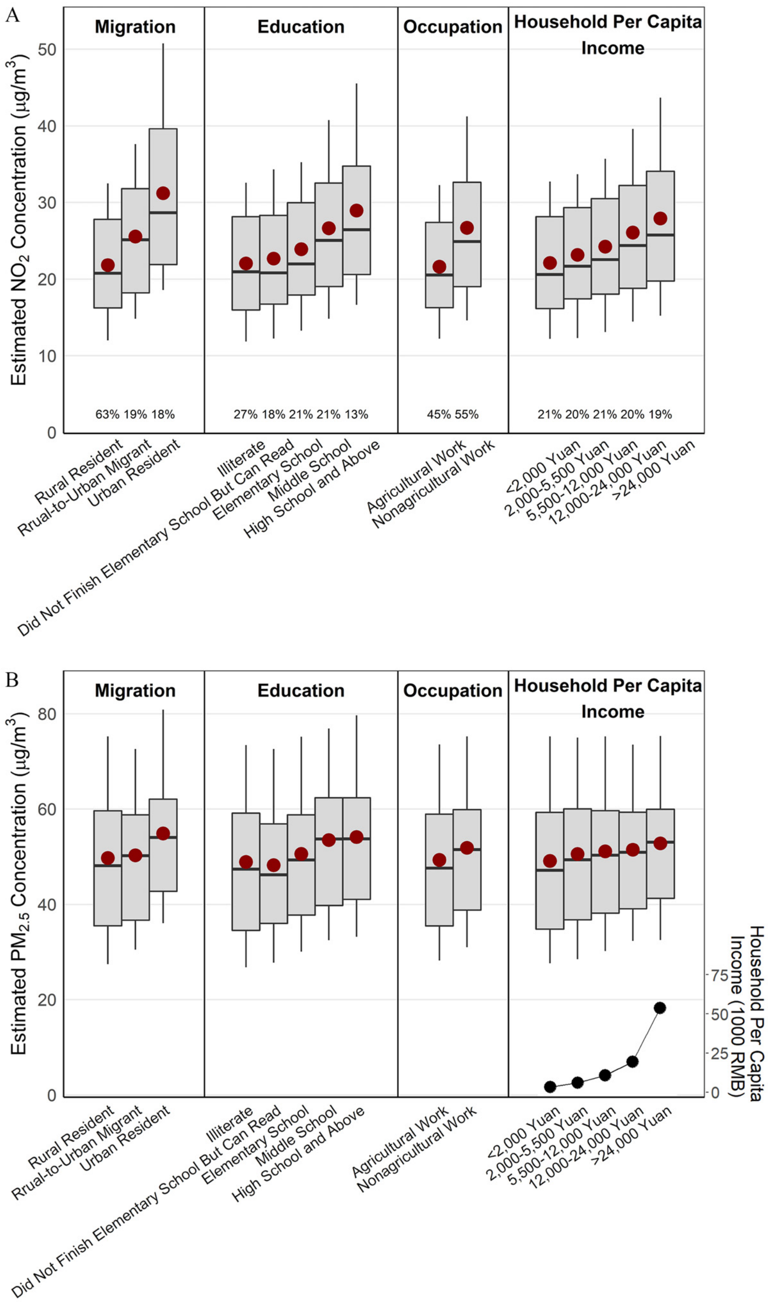

Figure 1. Estimated ambient (A) NO_2 and (B) $PM_{2.5}$ concentration by individual's rural-to-urban migration status, education, occupation, and income quintile. Box and whiskers indicate the 10th, 25th, 50th, 75th, and 90th percentiles and the mean (red circle). Income levels are displayed in the lower right of (B). The percentage numbers of individuals in each subgroup are annotated at the bottom of (A). Note: NO_2, nitrogen dioxide; $PM_{2.5}$, fine particulate matter, RMB, Renminbi.

Our core result—the positive relationships between ambient concentrations and SES—persisted even for dramatically different spatial units of analysis. Specifically, when averaging GDP per capita and air pollution concentrations across grid sizes from 1 to 100 km (i.e., from 1 to 10,000 km^2), slopes of best-fit lines (Figure 3; Figure S7) remained positive ($p < 1 \times 10^{-10}$). In general, disparities decreased with coarser resolution. This result is likely because the coarser resolution smooths out the spatial clustering of SES (Figure S8); similar findings were noted in the United States for modeled $PM_{2.5}$ concentrations (Paolella et al. 2018) and, generally, for empirical models of NO_2 and $PM_{2.5}$ (Clark et al. in prep).

Our results were robust to the use of monitored rather than modeled pollution concentrations (Tables S14 and S15). Specifically, the core result (positive relationship between SES and concentrations) generally held when using monitored or modeled concentrations at all monitored locations and at rural monitor locations; the results were not significant at urban monitored locations (after controlling for population density, the results for NO_2 became significant at urban monitored locations). For both pollutants, quantifications of that relationship (the relative concentration differences between highest and lowest 20% SES) differed <3% between monitored vs. measured data (Tables S14 and S15). That agreement in part reflects the strength of the models employed [R^2: 0.78 (NO_2), 0.89 ($PM_{2.5}$); root-mean-square-error: 5.9 $\mu g/m^3$ (NO_2), 6.3 $\mu g/m^3$ ($PM_{2.5}$)].

Discussion

Across several analyses, we found a positive relationship between SES and ambient air pollution in China: On average,

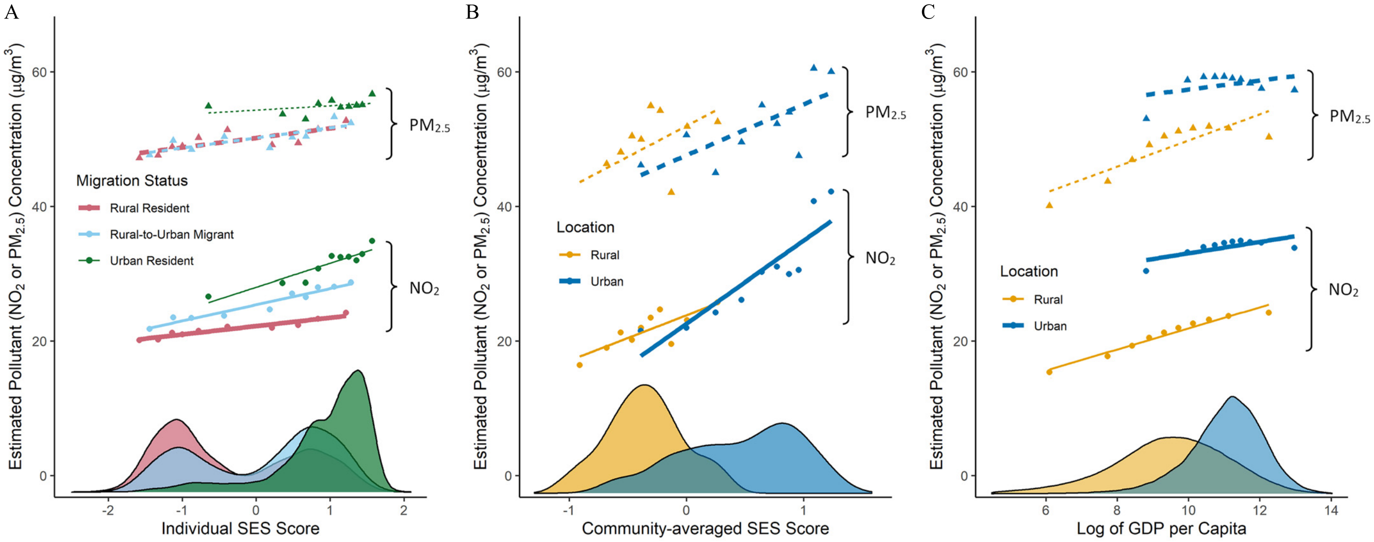

Figure 2. Relationship between SES and ambient NO_2 and $PM_{2.5}$ concentrations, based on (A) individual data, (B) areal data derived by aggregating the individual data to the community-level, and (C) areal data derived from national gridded GDP and world population density data sets. Data are plotted by urban–rural status, reflecting available data for individual data (A), three groups (rural resident, urban resident, and rural-to-urban migrant); for areal data (B,C), two groups (rural, urban). SES values reflect available data: (A) individual SES, (B) community-averaged SES, and (C) GDP per capita. Each plotted point represents the mean pollution concentration for 10% of the subsample. For example, in (A), the left-most red point represents the 10% of the rural residents with the lowest standardized SES score, and the right-most blue point represents the 10% of the rural-to-urban migrants with the highest standardized SES score. Plots also display best-fit lines and kernel densities. All of the best-fit lines have a positive slope {$p < 0.002$ in all cases, except one [$PM_{2.5}$ for urban residents in (A); $p = 0.48$]; for NO_2 in (B) and all conditions in (C), $p < 1 \times 10^{-6}$}, indicating that in all cases considered, higher SES is correlated with higher concentrations of ambient air pollution. Note: GDP, gross national product; NO_2, nitrogen dioxide; $PM_{2.5}$, fine particulate matter; SES, socioeconomic status.

NO_2 and $PM_{2.5}$ concentrations are higher than average for higher-SES populations and lower than average for lower-SES, rural-to-urban migrant, and ethnic minority populations. These findings are remarkably robust, holding for urban and rural locations, across nearly all geographic subregions within China, for three measures of SES (one individual measure, two areal measures), for modeled vs. measured pollution concentrations, for multiple definitions of urban vs. rural, and across a 100-fold range (in terms of area: 10,000-fold range) of spatial resolutions. Findings here are consistent with the hypothesis described in the

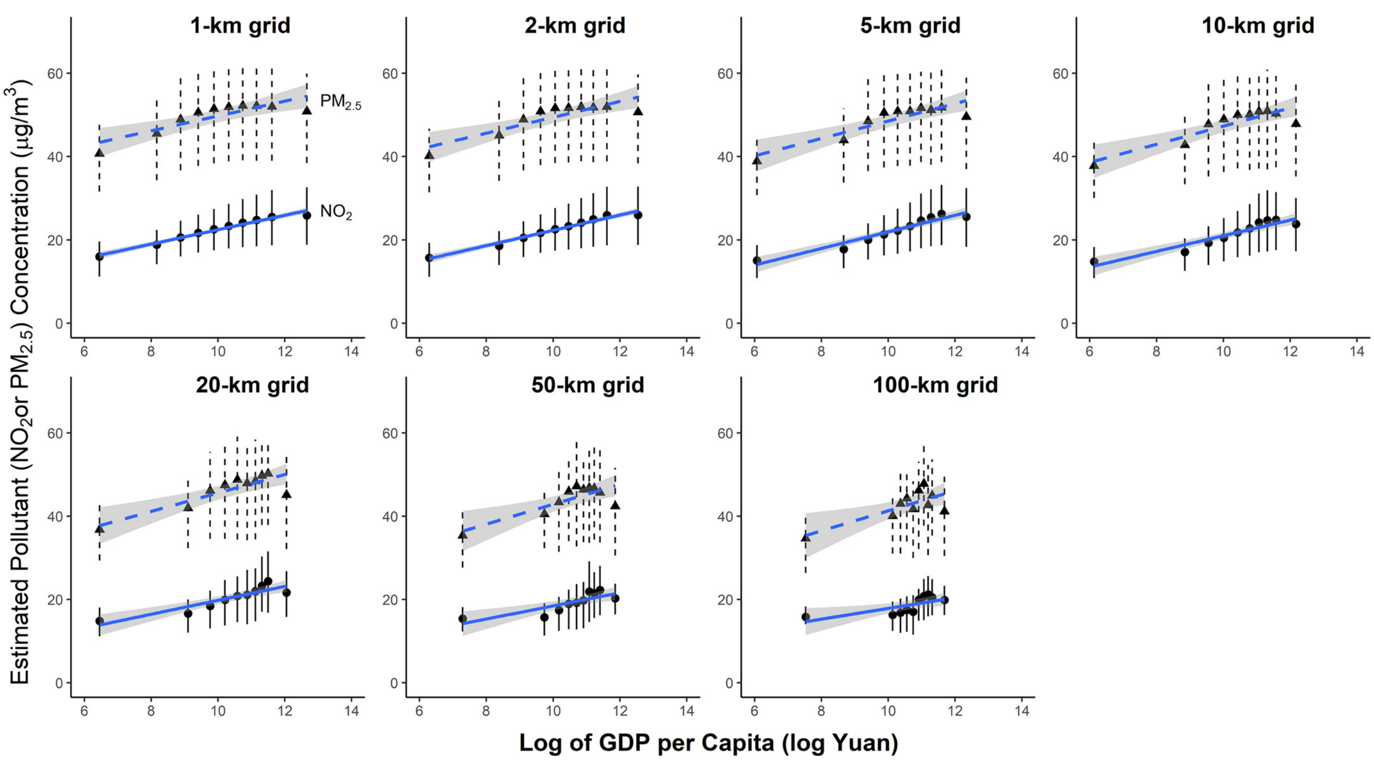

Figure 3. Relationship between pollution concentration and log GDP per capita, by grid cell size. Each point shows the mean log GDP per capita and mean pollution concentration of every 10% of population; each segment shows the IQR of pollution concentration. Best-fit lines by pollutant are shown in each plot. Note: GDP, gross national product; IQR, interquartile range; NO_2, nitrogen dioxide; $PM_{2.5}$, fine particulate matter.

"Introduction" section, that ambient air pollution exposures are higher for higher-SES than for low-SES individuals and areas.

Prior findings on air pollution and demographics in China (e.g., Norbäck et al. 2018; Xu et al. 2019b; Shen et al. 2020; Wang and Komonpipat 2020) have generally been inconclusive; in some cases, they propose an EKC relationship (e.g., for urban areas; Zhao et al. 2019b). (In general, this prior work employed census demographic data.) In contrast, findings here are consistent and monotonic.

Disparities are larger for NO_2 than for $PM_{2.5}$ (Tables S10–S13), likely reflecting the greater spatial variability for NO_2 than $PM_{2.5}$. NO_2 is a traffic-related pollutant of predominantly urban origin and is influenced by local emission sources; $PM_{2.5}$ has long-range and secondary components and thus varies at a regional level (Eeftens et al. 2015; Wang et al. 2020b). The larger disparities for NO_2 than for $PM_{2.5}$ are consistent with results from other countries (Clark et al. 2014, 2017; Liu et al. 2021; Su et al. 2009), likely reflecting spatial aspects of the two pollutants [i.e., greater spatial variability for NO_2 than for $PM_{2.5}$, owing to differences in the emission sources and atmospheric chemistry (e.g., the strong regional secondary component for $PM_{2.5}$)], which held in other countries too (Kim et al. 2020; Wang et al. 2020b).

We mainly explored rural-to-urban migration status and three SES measures in our study; in addition, we also considered the effects of ethnicity and of family living expenditures. Other unmeasured factors (e.g., industrial structure, housing price, and *hukou* policies in different cities and regions) may have also influenced our results. For example, on average, cities that rely more on secondary industry (i.e., manufacturing) may tend to have more industrial pollution ($PM_{2.5}$) than cities that mainly rely on tertiary industry (i.e., services), so even at the same income/GDP per capita level, the ambient pollution for their residents are different. Future work could explore those factors that are unmeasured here.

The positive pollution–SES relationship in China is generally the reverse of patterns typically reported in the literature, which in part reflects that the existing literature focuses mostly on the United States and, to a lesser extent, other high-income countries. This difference in results likely reflects the different cultures, economic and political systems, history, demographics, level of industrialization, and urban structure in China vs. the United States. Several examples of such are described in the "Introduction" section. For example, differences in urban characteristics tend to increase the proportion of *a*) high-SES populations that live close to the urban center and *b*) low-SES populations that live in the suburbs and exurbs (Guo et al. 2020; Wu 2002; Xiao 2016).

Our findings likely have implications for other locations besides China. Specifically, for countries that are (like China) relatively homogenous racially and with economic development that is relatively recent (past decades), results here suggest that exposures may follow a different pattern than has been observed for the United States. Future work can usefully explore patterns in other contexts to develop the underlying framework and look at changes over time. For example, without further evidence, we would be hesitant to ascribe our hypothesis to other points in time. If future economic development and urbanization is concurrent with improvements in air pollution—especially in high- and upper-middle-income counties in China (Wang et al. 2020a)—then current patterns of environmental inequality may change over time. In recent years, with economic reform increasing public pressures for clean production, increased public awareness of air pollution, and more complete and rigid environmental protection laws, both air pollution level and GDP growth rate are decreasing in China. Industries are moving from urban areas to rural/suburbs and from major cities to surrounding cities (Zhao et al. 2014); these patterns may, in the future, weaken or shift the relationship between SES and air pollution that is reported here. In addition, with continued rural-to-urban migration, lower-SES populations may increasingly move to the heavily polluted megacities (e.g., Beijing, Shanghai, Guangzhou) for work, which could also weaken the positive pollution–SES relationship. Environmental justice theory in the United States (Bullard 2008; Lerner 2010) and elsewhere (Castán Broto and Sanzana Calvet 2020; Valenzuela-Fuentes 2021) highlights the concept of sacrifice zones—locations that lack political power and receive disproportionately high environmental risks. This is a critical aspect of how relationships here might shift over time that will depend in part on inequities in political power and whether sacrifice zones become more prevalent.

Limitations of our methods include the following. First, we investigated ambient concentrations at home locations rather than personal exposures. This approach, which is common in the literature, omits factors such as mobility (e.g., travel for work and recreation), occupational exposure, and near-source exposures (e.g., environmental tobacco smoke; time spent on-roadways; indoor use of solid fuels for cooking, heating, or lighting) (Baccarelli et al. 2014; Baumgartner et al. 2011; Du et al. 2010, 2018; Sun et al. 2017; Venners et al. 2001; Xu et al. 1996; Zhao et al. 2006; Zhang et al. 2002; Marshall et al. 2003, 2006; Pant et al. 2017; Milà et al. 2018). Future work could shed important additional insight by considering those factors. [Some of the factors are already well studied, e.g., indoor use of solid fuels for cooking generally happens in lower-income, not in higher-income, households (Chan et al. 2017; Duan et al. 2014; Muller and Yan 2018).] Second, two of the three SES metrics are derived from CHARLS, which is a cohort of individuals $\geq$45 years of age that is representative of that age group but is imperfectly representative of the overall (i.e., all ages) Chinese population (Table S16). (The third SES metric, derived from gridded GDP data, does not face this limitation.) Third, our methods do not reveal which emission sources drive the concentrations and inequalities; future work could usefully investigate this question (Geng et al. 2021; Ji et al. 2015; Rao et al. 2021; Zhao et al. 2019a). Fourth, our methods do not employ a spatial regression approach; future work could shed additional insight by accounting for the spatial clustering of air pollution (Zhang et al. 2021). Fifth, we studied conditions in China and not in other countries. Future studies could usefully address this point by, for example, using a unified definition of SES and exposures to compare across multiple countries.

Our study describes a framework of air pollution inequality in China and uses several approaches to testify our hypothesis. Strengths of our approach include use of multiple data sets and lines of evidence, including multiple approaches to estimating SES; investigation nationally, comprehensively, and for several subpopulations (e.g., subnational region; migrant status) using consistent methods; comparing across two pollutants, with good spatial precision; use of modeled as well as measured concentrations; use of global population density data and cohort data on demographics and home-location, which improves the spatial precision of the demographic information and decreases the spatial aggregation problem (Paolella et al. 2018; Bowen 2002; Maantay 2002; Clark et al. in prep); and sensitivity analyses that consider multiple perturbations to the core analyses [e.g., a 100-fold (by area, a 10,000-fold) change in spatial resolution; use of different definitions of urban vs. rural]. The multiple approaches and sensitivity analyses reveal similar core findings, which adds confidence regarding the robustness of findings.

Conclusion

This study finds that for two important air pollutants (NO_2 and $PM_{2.5}$), average ambient exposures in China are higher for higher-SES than for lower-SES populations and higher for long-standing urban residents than for rural-to-urban migrant populations. The results are robust to using multiple individual- and areal-level SES approaches, in both rural and urban locations, across geographies, across a 100-fold range of spatial resolution, and for monitored vs. modeled ambient concentrations. The disparity for NO_2 is larger than for $PM_{2.5}$.

Our results are consistent with our hypothesis, which is the opposite of most of the existing environmental justice literature; findings here likely reflect correlations among economic development, SES, and pollution (i.e., economic development increases SES and pollution levels). Our findings may have implications for locations outside of China, especially for other low- and middle-income countries.

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